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Willingness to pay for solar adoption: Economic, ideological, motivational, and demographic factors

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ABSTRACT

Residential solar energy installations are a critical component of the energy transition. Nonetheless, just a small fraction of all eligible households have installed solar panels. We investigate household willingness to pay (WTP) for a residential rooftop solar system using a stated preference approach and including socio-demographic, ideological, economic, and psychological factors.

We implemented an online survey of 580 households in New York State who had not previously adopted a residential solar system. Respondents were presented with hypothetical PV systems with varying upfront costs and monthly savings that allow us to understand discount rates and payoff preferences. This allowed us to explore not only WTP and how it varies across the factors described above, but also how those factors affect discount rates and attitudes towards uncertain future payoffs from the systems. We limit our analysis to New York to control for variation in solar adoption policies from state to state, but these results are broadly generalizable to other US States and, with caveats, to advanced industrialized democracies.

We find an average WTP of $7388.5 for installing a residential rooftop solar system. Respondents' WTP is $11.66 in upfront costs for each additional $1 of average monthly savings. We also find substantial heterogeneity in WTP and in trade-offs between upfront costs versus savings. Age, children in households, income, education, motivation, and ideology are all independent factors associated with WTP. We discuss a range of implications for policy and marketing to further increase rates of adoption in the future.

1. Introduction

The adoption of solar energy is a critical part of the clean energy transition necessary to avert the worst effects of climate change. Between 2014 and 2022, residential solar energy capacity grew by a factor of 5.4 with almost 40GW of capacity now installed (Energy Information Administration, 2023). However, much more solar will be needed to implement the energy transition. Residential rooftop solar has additional potential benefits compared to utility scale solar and other renewable electricity systems because it is distributed in nature. This reduces needs for transmission and distribution, and can increase resilience in the context of higher weather variability and intensity associated with climate change (Astier et al., 2021; Luke, 2020; Ihnen, 2016; Carley, 2009; Pepermans et al., 2005; Barker and De Mello, 2000). Policymakers have used a wide array of incentives to influence residential solar adoption. Understanding how these incentives work and what specific variables affect solar adoption is critical to accelerating a clean energy transition.

A variety of studies have examined the adoption of residential rooftop solar, but very few address willingness to pay for this amenity. In particular, our survey uses discrete choice experiments to determine willingness to pay across several critical payment variables. Better understanding of these preferences can be useful for specific aspects of policy design, and for the understanding of the customer market. Researchers have found a variety of factors that influence adoption including building infrastructure, tree cover, aesthetics, cost, payback, incentives and subsidies, psychological factors, ownership status, and many more (EzzEldin et al., 2022; O'Shaughnessy, 2022; Sun et al., 2020; Zander et al., 2019). Some of these factors can be considered in policy design, to improve adoption rates overall, and specifically to target rural, vulnerable, or low-income populations. This research adds to the literature in this area by considering demographic, ideological,

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and psychological variables and integrating them with economic considerations.

This paper proceeds first by reviewing many of the key factors that drive adoption of rooftop solar with extensive discussion of some of the critical economic, logistic, and socio-economic factors that we include in our survey and study. We then briefly review some of the specific issues in discrete effects contingent valuation analysis. We describe the development of our survey and research design, and discuss some of the most relevant findings.

2. Adoption and WTP for residential rooftop solar

One of the biggest challenges in understanding a phenomenon as complex as the decision to install rooftop solar is that there are so many different factors that can affect the decision. Broadly, this includes economic, regulatory, geographic, regional, socio-economic, psychological, and belief orientations of a potential adopter. The solar adoption decision is also influenced by peer effects (existence of neighbors/ friends who are adopting solar), technological, cultural, and environmental values. We list a wide variety of factors that influence the solar adopter decision in Table 1 below.

The literature cited in Table 1 shows that one of the most significant factors to affect adoption is cost. However, cost can manifest in a variety of different ways. It may manifest in the initial cost for an installation, monthly payments over time, and impacts on utility bills. Monthly payments can vary in years and amortization. Cost factors are complicated by the attempt to determine the amount of savings that will accrue on a yearly or monthly basis in terms of reduced electricity payments. Finally, the value of solar systems is further affected by a series of non-market amenities in terms of resilience, environmental impacts, transaction costs, or other factors.

Table 1
Economic, Logistical, and Demographic Factors for Residential Solar Adoption*

Economic	· Income · Home ownership · Upfront installation cost or down payment · Ongoing monthly payment to the developer · The amount of savings on the monthly electricity bill · The length of the payoff period · The time when savings overtake costs · Whether production amounts are guaranteed; production in rainy or winter seasons · Effects on home value · Targeted low-income incentives
Physical & Infrastructure Characteristics	· Roof structure area or strength or design · Yard or open area available · Building orientation · Tree cover
Geographic	· Solar exposure in specific location and region
Logistical / Transaction Costs	· Homeowner moving or instability · Ease of hiring a solar installer · Vetting, permitting, or training of installers · Length of time to schedule installation · Amount of paperwork or bureaucracy involved in qualifying and installing a system
Regulatory	· Neighborhood zoning · Policy outreach, communication · Options for leasing, or PACE (property assessed clean energy loans) · Solar Renewable Energy Credits (SRECs)
Social and Demographic Characteristics	· Gender · Ideological beliefs · Political Affiliation · Environmental beliefs · Age · Lack of knowledge in rural areas · Peer Effects / neighborhood adoption
Aesthetic	· Willingness to reduce tree cover · Concerns for viewshed

* Sources include Zander et al., 2019; EzzEldin et al., 2022; O'Shaughnessy, 2022; Sun et al., 2020; Karakaya and Sriwannawit, 2015; Lo et al., 2018; Forrester et al., 2022

2.1. Stated preference methods

These are a well-known technique used in environmental and health economics to measure willingness-to-pay (WTP) for non-market goods, policies, and services. They show how respondents value environmental and other goods that are not traded in traditional market settings (i.e., clean water, clean air, landscape, rivers, etc.). The two primary approaches are contingent valuation (CV) and discrete choice experiments (DCE). The differences between these two methods stem from the approaches taken to eliciting stated values. Both use survey data with hypothetical scenarios in which respondents express their WTP for explicit non-marketed goods or their willingness to accept (WTA) to give up those goods.

In general, the contingent valuation method asks people referendum-style questions such as, "If the described policy [or good] would cost your household $X, would you prefer that policy?". Many researchers have used CV to explore WTP for green electricity (Mozumder et al., 2011; Yoo and Kwak, 2009; Zhang and Yang, 2012). Alternately, discrete choice experiments present a series of choice sets to respondents where they can compare two or more programs (i.e., service, policy, or goods) with various levels of the program's attributes. In each choice set, respondents are asked to choose the preferred program or service out of those presented to them. The DCE approach has also been used to estimate WTP for green energy (Bao et al., 2020; Borchers et al., 2007; Goett et al., 2000; Mabile, 2021). An advantage of the discrete choice approach is that it allows policymakers to understand, prioritize, and understand the value of particular attributes or services associated with a given policy action or program (Guerrero et al., 2020).

Both CV and DCE methods have been extensively used to estimate the residents' willingness to pay (WTP) for green electricity/ renewable energy in many countries. Appendix 1 shows Table I-5 that presents a summary of existing research. Our research adds to past analysis because it includes specific program attributes associated with solar adoption, improves the rigor with which we identify survey respondents who actually could adopt solar, and includes a larger variety of relevant contributing factors.

Very few researchers use discrete choice experiments to estimate WTP for residential rooftop solar systems. Mamkhezri et al. executed a choice experiment survey in New Mexico to study consumer preferences and their preference heterogeneity (Mamkhezri et al., 2020). They found positive marginal willingness to pay (MWTP) for rooftop solar and smart meter installation, with variation between rural and urban households. Another choice experiment surveyed two U.S. cities and showed that a neighbor's installation, the described environmental benefit of the installation, and economic savings all had a positive effect on rooftop adoption. Upfront cost was a significant barrier and WTP ranged from $4700 to $5500 (Mabile, 2021).

The upfront installation cost of a solar home system is a major hurdle for most consumers. Abdullah et al., studied the public acceptance and willingness to pay for solar home systems (SHS) in Pakistan. They found that 81% of the respondents were very interested in SHS' in Pakistan and 77% of the respondents were willing to pay for the SHS if the government subsidized half of the upfront installation cost of the solar system (Abdullah et al., 2017). Other studies have similarly found that government incentives have a substantial influence on intention to adopt rooftop photovoltaic adoption (Lan et al., 2021; O'Shaughnessy, 2022; Sun et al., 2020).

High up-front costs are a major factor in low solar adoption particularly with uncertainty in the future benefits and payback period (Bauner and Crago, 2015). However, Matisoff and Johnson (2017) suggest that a variety of policies that reduce up-front costs can be particularly effective at the state or federal level. These include third-party ownership or leases, low-cost loans, and other policy incentives specifically designed to address up-front cost.

Gillingham and Tsvetanov (2019) show that the estimated price elasticity of demand is −1.76 from 2008 to 2014 in Connecticut. In simple terms, lowering solar system price by a $1/W results in 1102 more installations. Their research also showed that dropping incentives and eliminating municipal permit fees would have reduced solar installation.

2.2. Additional factors for understanding solar adoption

As of 2018, only 3.1% of global electricity is generated from solar PV (IEA, 2020). Two tandem goals for policymakers are to improve the capacity of rooftop solar PV technology and to increase the rate of adoption of rooftop solar. Che et al. evaluate both innovation and adoption in a study of regional policies for PV technology innovation (Che et al., 2022) by evaluating patents generated across 260 cities in China from 2007 to 2018. They find that an even mix of policy types at the city level increases innovation. They examine i. supply-side (research subsidies, public service, infrastructure construction, and training); ii. demand-side policies which promote the markets that PV is being sold into via feed-in tariffs; and iii. procurement, and environmental policies that support regulations and finances for environmental goals that also motivate PV development. While many of these policies are evaluated in terms of technological innovation, they are ultimately relevant to adoption as well.

Changes or modifications in policies can also have an effect. For instance, Zander et al. investigate the impacts of changes in incentive policies on willingness to adopt residential rooftop solar in Australia (Zander et al., 2019). Approximately two-thirds of respondents would want to install solar despite reductions in incentive policies. In earlier years of solar adoption, policies were not as effective. Bauner & Crago show that federal and state incentives lowered the upfront cost of residential solar systems by over 50% in Massachusetts in 2012 (Bauner and Crago, 2015). Still, only 0.5% of households in Massachusetts adopted solar at that time but they show that rebates and tax credits decrease adoption times.

The challenge of solar adoption is even greater in the developing world. Lan et al. explore the household intention and willingness to pay for a rooftop solar electricity system in a regional province of Vietnam (Lan et al., 2021). By late 2019, only 18 households had adopted a rooftop solar system out of 435,688 households. Willingness to pay survey data showed a range of $1240 to $2220 (US) for a rooftop system, far less than the actual cost of a system install. Quite simply most households did not have enough income and capital to adopt. Government incentives and household attitudes emerge as the most important factors for the intention to adopt solar. Environmental concerns and the innovativeness of households were less influential factors.

2.3. Socio-demographic, motivational, and ideological factors

Research on the individual predictors of solar adoption and adoption intentions is growing steadily. For instance, solar adopters generally have more education and higher income than the average citizen (Alipour et al., 2020) and tend to live in more urban centers (Barbose et al., 2021). The motivational determinants of adoption are quite varied – with some studies suggesting solar adopters score high in pro-environmental concern (e.g., Fikru, 2021; Schelly and Letzelter, 2020; Wolske et al., 2017) and others indicating adoption is more strongly connected to the desire to signal a positive self-image and status (e.g., Noppers et al., 2016). The desire to use solar panels to signal status may be related to normative social influence (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2014). Specifically, Graziano and Gillingham's show a peer effect demonstrating that residents adopt solar if nearby neighbors have a system. Bollinger et al. have shown that peer installations influence adoption up to 500 m on the same street (Bollinger et al., 2022). Similarly, Corbett et al. (2022) note that "place attachment," (i.e., respondents' attachment to their community) positively influences rooftop solar adoption.

The underlying value of solar energy as "green" source of energy is also a major factor. Existing research shows a positive WTP for the underlying value of green energy (Mozumder et al., 2011; Zhang and Yang, 2012; Nomura and Makoto, 2004; Borchers et al., 2007; Mabile, 2021). Komarek et al. (2011) found a positive WTP for carbon emissions reduction associated with solar adoption. Similarly, a study in Sweden shows positive WTP for green versus fossil derived electricity (Hansla et al., 2008). This prompts our use of the psychological factors in environmental motivation as a component of our research.

Ideological beliefs are also a factor. Research by Mildenberger et al. suggest that Democratic households are slightly more likely to adopt a rooftop solar system (Mildenberger et al., 2019). Given extreme partisan belief systems surrounding green energy, they find that the adoption difference is not quite as extreme as we might expect but is still significant.

Sun et al. differentiate between attitudes towards solar versus intention to adopt. These include personal traits, psychological benefits, government incentives, attitude towards rooftop PV installation, and intention to adopt PV (Sun et al., 2020). They found that personal characteristics and psychological benefits impact the *attitude* towards solar adoption, but government incentives strongly influence the *intention* to adopt rooftop PV.

Overall the literature addresses a broad range of factors that can potentially influence solar adoption. This paper focuses primarily on identifying prospective adopters' willingness to pay for solar panels, as well as the extent to which WTP changes as a function of demographic, logistical, and ideological factors. Our work addresses additional psychological factors more extensively in another paper under development.

2.4. State and federal policies in New York

Our survey work is located in the state of New York as a way to control for variation in policies across different U.S. States. We provide an overview of many policies that address costs in a variety of ways in New York, including incentive programs, tax credits, and rebates. Table 2 shows detailed information on federal, state, and New York City policies in place at the time of our survey.

3. Survey instrument and research design

This study uses a discrete choice experiment (DCE) method and mixed logit model to estimate the household WTP for a residential rooftop solar system. The DCE method is based on the random utility theory developed by McFadden in the 1970s (Domencich and McFadden, 1975; McFadden, 1996, 1974). In random utility theory consumers choose amongst alternatives by considering the attributes of the goods and the related prices to maximize their utility (Lancaster, 1966; Sammer and Wüstenhagen, 2006). The observed choice is considered a random variable since the analyst does not have full information about the respondent's utility of each alternative.[1]

In our model, the alternatives that respondents face are different configurations of residential solar installations. These configurations vary along four economic dimensions, but are assumed to be the same on physical dimensions (power output, number of panels, etc.). Based on

[1] See Appendix 2, The Discrete Choice/Random Utility Framework, for more details.

Table 2
New York State Solar Energy Policy Overview.

Policy/Incentive Program	Overview/Value
Federal	
Federal Solar Investment Tax Credit (ITC)	All U.S. residential homeowners gain a 26% federal tax credit if they installed solar systems by December 31, 2022. Generally, a 5-kW (kW) system costs $14,994 in New York.[a]
NY State	
NY-Sun Incentive Megawatt Block Program	This program offers qualified homeowners up to $1000 for every kilowatt (kW) of solar system installed.
New York State Solar Equipment Tax Credit	All installations qualify for a solar equipment tax credit of 25% of the system's total installation cost (Max. $5000).
Home Solar Project State Sales Tax Exemption	New solar systems are exempt from state sales tax on the equipment, saving 4% of total costs.
Solar Electric Generating System Tax Abatement (SEGS)	New York State homeowners receive property tax exemptions on new solar and storage systems, typically increasing home value up to 4.1%
New York State Historic Homeownership Rehabilitation Tax Credit	Only eligible historic homeowners are eligible for this tax credit which can reduce the cost of the solar system by up to 20%.

[a] This valuation was determined in Dec. 2022 using the *sunrun.com* valuation approach for a typical 5 kw system (the median value of the average range of solar rooftop installations in the US at that time).

the random utility framework, respondents are asked to choose the hypothetical system which they prefer, or to choose not to install a system at all - whichever maximizes their utility.

3.1. Valuation attributes, and levels

In the Table 3 below, we show the valuation attributes and levels for upfront installation cost, monthly savings, and degree of uncertainty for savings. For each one we determined a mid-range expectation based on New York state installation expectations and generate ranges in monthly savings expectations to simulate the lack of certainty on saving levels that occurs with a solar installation. We assume a 20-year life expectancy on the system, though some new systems now have 25-year life spans. We focus on monthly savings per Dong and Sigrin (2019) because billing occurs at the monthly level, and that is how residents understand their monthly spending.

It can be a challenge to determine the optimal allocation of attribute levels while still allowing for a design size within the practical limits of survey design. We use orthogonal fractional factorial design to develop the choice experiment. Given the many attributes and their corresponding levels, there would be 36 possible combinations of scenarios if we used full factorial design (3*4*3*1). We use fractional factorial design to develop a smaller design size. This is generated using an SAS macro by (Kuhfeld, 2010).[2] The final ranges used in the survey are shown below in Table 3.

Table 3
Attribute and levels.

Attribute	Levels
Upfront Installation Cost	$2500; $5000; $10,000
Expected Monthly Savings on your Electricity Bill	$75; $100; $125; $150
Range of Monthly Savings on your Electricity Bill	$0; $50; $100[a]
Lifetime of System (years)	20

[a] The two attributes of expected monthly savings and range of monthly savings combine in the creation of the survey choice sets to produce what is labeled as "expected monthly savings" in the choice set. For instance, when the respondent sees expected monthly savings of $75, this is, in our nomenclature, a combination of the two attributes Expected Monthly Savings = $75 and Range of Monthly Savings = $0.

Table 4
Choice Question Example.

	Install A	Install B	Don't Install
Upfront Installation Cost	$2500	$5000	$0
Expected Monthly Savings on your Electricity Bill	$100	$50–$150	$0
Lifetime of the System (years)	20	20	–

The survey asks respondents to choose between two installation configurations (Install A or B) or the status quo alternative (i.e., Don't Install). The final design includes 18 choice questions, broken into 3 blocks of 6 choice questions each. To reduce survey fatigue, each respondent was randomly assigned 6 out of the 18 possible choice questions. Table 4 below presents one example of a choice question asked in the experiment.

3.2. Survey implementation and respondent data

Our survey was conducted as an online panel survey and executed using two different survey platforms (Qualtrics, SurveyMonkey) in 2019. Respondents were 18+ years old, owned a residence in New York State (renters excluded), did not already have a solar installation, and had familiarity with the electricity bill. We had an N of 613 solar non-adopters, and after omitting respondents for data quality, straight-lining, and other concerns, end up with a final N of 580. Further information on our data cleaning procedure is included in Appendix 1, Table I-1.

Our choice to work only in New York State was to control for varying solar policies in other states which could complicate our results. New York is also a useful choice because it has substantial variation in housing types and geography, and has an extensive non-urban population that could potentially adopt solar at the household level. That said, our findings are likely transferable (with some variance and appropriate caveats) to other states and other advanced industrialized democracies with similar challenges in expanding rooftop solar.

Our primary requirement with Qualtrics and SurveyMonkey for sample design/collection was that it should be aligned with the demographics of the New York state population. Appendix Tables I-2 and I-3 show that most demographics were aligned very well with the population of New York State. In our sample, Gender, Income, Education, Age, Ethnicity, and Political views align well with New York state population data. We under sample very high-income and less-educated people (less than a high school degree). We also somewhat oversample white, young, higher educated (college graduate), and households with children.

In addition to the discrete choice valuation questions, we also included questions concerning environmental motivation, ideology and party identification, and socio-demographic variables. An ideology score derived from the Pew Research Center's American Values Survey (Kohut et al., 2012) was calculated based on the average of respondent's answers to questions regarding their views on economic (taxes, government spending and programs) and social issues (religion, civil rights, civil freedoms). Ideology is likely to affect an individual's valuation of new "green" energy sources such as solar energy. An extensive literature exists that demonstrates the relationship between political views and aspects of energy systems (Sherman et al., 2016; Gromet et al., 2013; Cherp et al., 2018; Breetz et al., 2018). Specifically, more conservative individuals may be more likely to view themselves as self-reliant, but also be less likely to support community investment in new energy

[2] Sahan Dissanayake at Portland State University was instrumental in creating this experimental design.

technologies associated with climate change, and be less supportive of institutional or government mechanisms associated with decarbonization or the clean energy transition.

To assess environmental motivation, we used three dimensions from the *Motivation Towards the Environment Scale* ((MTES) Pelletier et al., 1998; Sherman et al., 2016) using autonomous motivation (intrinsic & integrated) and external motivation. Those with autonomous motivation are concerned with helping the environment because it is inherently satisfying or personally important. In contrast, those with external motivation try to engage in proenvironmental behavior because they think it's expected of them or because they feel pressure from others. Examples are shown in Table 5 below.

A long line of research has shown that autonomous reasons underlying environmental decisions and behaviors is associated with more frequent and long lasting proenvironmental effort (Legault, 2023). However, the role of motivation in predicting WTP is not yet known. Participants were asked to rate the extent to which each item in the index corresponded to their personal motives for potentially adopting solar on a Likert scale. An example question showing autonomous motivation is, "because being environmentally conscious has become a fundamental part of who I am." External motivation is focused on external factors for action (e.g., "because other people will be upset if I don't do things for the environment"). Finally, amotivation is measured by questions such as "I don't really know; I can't see what I'm getting out of it." The factor structure of the MTES has been validated by exploratory and confirmatory factor analyses (cf. Pelletier et al., 1998). In addition, we asked questions concerning financial risk-taking and attitudes towards innovation that previous work has indicated are relevant to the question of adoption.

Finally, we examine socio-demographic factors such as race, income, gender, children in household, and age. Fathallah and Pyakurel have shown that gender is a significant dividing factor in energy actions and attitudes (Fathallah and Pyakurel, 2020). Similarly, Hotaling et al. show increased probability of women to pay for community microgrid development (Hotaling et al., 2021). Race and income are obvious factors to include given the challenges of solar adoption without significant economic resources. Finally, both parenthood and age are factors when considering long-term environmental impacts of climate change which stretch out over decades (Milfont et al., 2020; Bird and Lachapelle, 2019). For older respondents, they are unlikely to see the worst impacts of climate change. Alternately, households with children may be more concerned for the future. Descriptive Statistics for the survey are shown in Appendix 1, Table I-2, I-3, I-4.

Table 5
Environmental Motivation, Risk, and Innovation Question Types.

Attitude and Psychological Question Types	Description
Integrated motivation	· Taking care of the environment is an integral part of my life. · Taking care of myself and taking care of the environment are inseparable. · Being environmentally conscious has become a fundamental part of who I am.
Intrinsic motivation	· For the pleasure I experience while mastering new ways of helping the environment. · For the pleasure I experience while improving quality of environment. · For the pleasure I get from contributing to the environment.
External motivation	· Because other people will be upset if I don't. · For the recognition I get from others. · To avoid being criticized.
Financial risk	· Investing 10% of your annual income in a moderate growth diversified fund. · Investing 5% of your annual income in a very speculative stock. · Investing 10% of your annual income in a new business venture.
Innovativeness	· I must see other people using new innovations before I will consider them. · I tend to feel that the old way of living and doing things is the best way. · I seek out new ways to do things. · I frequently improvise methods for solving a problem when an answer is not apparent.

4. Results and discussion

The empirical analysis divides into two parts. First, we discuss the estimation results of preferences for the attributes using the general Mixed Logit model and estimate WTP for our proposed rooftop solar systems. Then we explore the same model including interaction terms to explore preference heterogeneity across respondents and illustrate these results with a series of "split-sample" estimates of WTP which suggest the kinds of preference heterogeneity that exist in our sample.

4.1. Estimation results using mixed logit models

We use a Mixed Logit model to estimate results. Mainly, we are interested in the ratio of β_k and β_{price}, which tells us the respondent's willingness to pay for the rooftop solar system (Revelt and Train, 2000). In addition, we are also interested in many of the other factors which help us better understand the respondent's behavior by considering the different demographic, environmental concerns, political affiliation, ideological and psychological factors on the decision to adopt a rooftop solar system. The mixed logit model results are summarized in Table 6. We use the sample of 580 households in New York State who had not previously adopted a residential rooftop solar system. In the survey design, we presented 6 choice sets to each respondent and asked them to pick one choice from three options. We run a mixed logit model using 10,440 observations (i.e., 580 multiplied by 6 choice sets by 3 choices) to estimate WTP results. There are six missing values for choices; therefore, in table 6, we have 10,434 observations.

Table 6 presents our estimation results for two models. The difference between the two models is the inclusion of the alternative-specific constant (ASC) which is a general measure of the likelihood of choosing a solar installation versus the default (status quo) choice. Model 1 includes attributes and the ASC. Model 2 omits the ASC. All attributes are

Table 6
Mixed logit model estimation results.

Variables	Model 1		Model 2	
	Mean	Standard Deviation (SD)	Mean	Standard Deviation (SD)
	(1)	(2)	(3)	(4)
Upfront Installation Cost	−0.00049*** (2.09e-05)		−0.00038*** (1.69e-05)	
ASC	3.625*** (0.302)	3.933*** (0.330)		
Average Monthly Savings	0.00572***	0.0215***	0.0232***	0.0269***
	(0.00199)	(0.00283)	(0.00160)	(0.00140)
Range Monthly Savings	0.000636	0.00760***	0.00391***	0.00921***
	(0.000819)	(0.00154)	(0.000822)	(0.00130)
AIC	5484.87	10,434	5927.95	10,434
BIC	5535.64		5964.214	
Observations	10,434		10,434	
Log-Likelihood	−2735.44		−2958.98	
LR Chi^2	1642.98		1293.26	

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level; standard errors in parentheses.

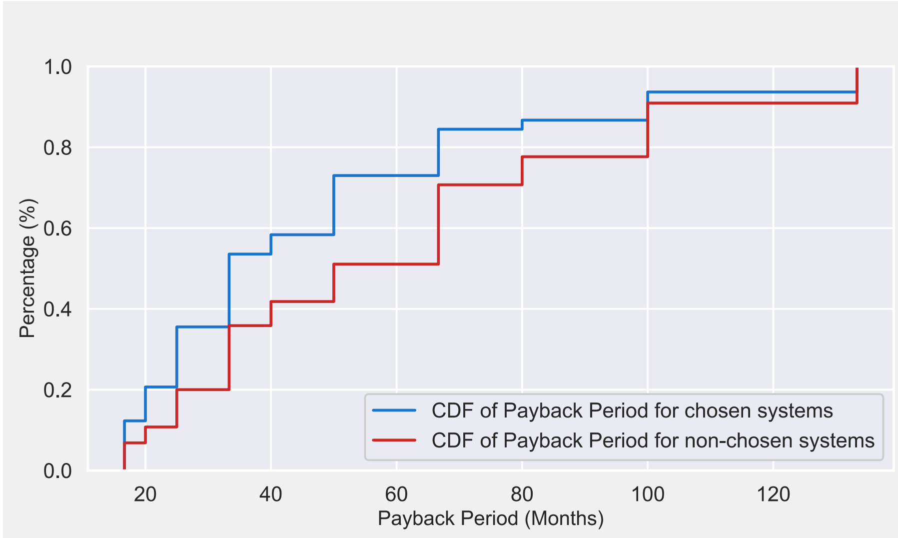

Fig. 1. CDF of Payback Period for non-adopters.

statistically significant at the 1% level in both models except for monthly savings range in Model 1. Unsurprisingly, a respondent's probability of choosing a solar system decreases as the upfront installation cost increases. The positive ASC suggests a positive WTP for solar installations, independent of characteristics. Similarly, "Average Monthly Savings" is positive. Not surprisingly, the larger the savings associated with a system, the more likely it is to be chosen by respondents.

We originally hypothesized that the coefficient on "Range Monthly Savings" would be negative since risk-averse consumers would, all else equal, prefer less uncertainty about their savings. However, this is not what we find. We find a positive coefficient in both models that is significant in Model 2 without the ASC. It shows that respondents have a positive willingness to pay for systems with higher uncertainty about monthly savings. A possible explanation is that the possibility of higher savings weighed more heavily in the decisions than the uncertainty or risk of lower savings.

One way to visualize expressed preferences for upfront costs vs. monthly savings is to look at payback periods. The payback period for an investment is simply the upfront cost divided by periodic savings to get the number of periods before the investment has paid back its upfront cost. In Fig. 1, we compare chosen systems to those left unchosen and display the Cumulative Distribution Function (CDF) for the payback period of each group. The blue line is the CDF of the payback period for chosen systems, and the red line is the CDF of the payback period for non-chosen systems. This visual makes clear that respondents definitely prefer systems with shorter payback periods and are more likely to choose those.

In Table 7 below we calculate WTP for solar systems and their attributes using the Krinsky-Robb method with 15,000 simulation draws based upon the mixed logit estimates reported in Table 6 (Hole, 2007). This method allows us to estimate both an average WTP and a 95% confidence interval. In column 1, the central estimate willingness to pay result is $7389 for a rooftop solar system (95% CI: $6276–8540). Column 2 shows that for each additional $1 of average monthly savings, respondents are willing to pay $12 upfront when we include ASC, and when we exclude ASC, that estimate increases to $61. With the ASC this implies an annualized discount rate of approximately 103%, while without the ASC (model 2), the corresponding estimate is approximately 19%. Existing studies of consumer behavior have suggested an average annual discount rate ranging from 39 to 51% across the different models (Epper et al., 2020). Some studies, using stated preference approaches, have also found large variation in estimated discount rates in similar contexts to ours - up to 559% - for different goods (Frederick et al., 2002; Howard et al., 2021; Vásquez-Lavín et al., 2021; Echeverría et al., 1995; Brouwer et al., 2008). Our estimates are in this, admittedly, very wide range.

Table 7
Willingness to pay results with confidence. Intervals for model 1 and model 2 are in Table 6.

		ASC	Average Monthly Savings	Range Monthly Savings
		(1)	(2)	(3)
Model 1	WTP	$7389	$11.66	$1.30
	Lower	$6276	$3.71	-$1.99
	Upper	$8540	$19.39	$4.55
Model 2	WTP	–	$60.93	$10.28
	Lower	–	$54.35	$6.07
	Upper	–	$67.65	$14.43

In general, the literature reveals that individual consumer discount rates have noticeable variation, are higher than the market, and vary widely across different studies and contexts. Many studies use different exogenous and endogenous approaches to estimate the discount rate. Howard et al. examined six different methodologies and found a 200% discount rate using a mixed logit model and DCE method (Howard et al., 2021). Similarly, some other studies found a high discount rate using CV and DCE methods. For example, 15–104% (Egan et al., 2015), 20–131% (Kim and Haab, 2009), 122–227% (Lew, 2018), 50–270% (Stevens et al., 1997), 60–340% (Vasquez-Lavín et al., 2019), 141–315% (Wang and He, 2018), 351–837% (Myers et al., 2017).

Loewenstein and Thaler state that 17%, 102%, 138%, and 243% annual discount rates have been associated with an investment in room air conditioner, gas water hear, freezer, and electric water heater, respectively (Loewenstein and Thaler, 1989). However, discount rates vary for some other environmental goods, such as for watershed restoration 15–104% (Egan et al., 2015), protecting migratory shorebirds 351–837% (Myers et al., 2017), protecting beluga whales 122–227% (Lew, 2018), and water quality and landscape improvements 141–315% (Wang and He, 2018). A high discount rate can be justified by consumers' intertemporal choice preferences, inflation, uncertainty, lack of time–money tradeoff skills, expectations of utility changes, and other confounding influences (Frederick et al., 2002).

The differences between models with and without the ASC suggest that we are not able to separately identify people's WTP for rooftop solar installations from the economic benefits that are associated with those systems. Thus, when we do not allow for the constant term, much of the associated WTP transfers to the system attributes, especially the Average Monthly Savings associated with the systems. Our WTP estimates are similar to a previous study by Mabile (2021) that found household WTP in Atlanta and Boston to $4700 and $5500 for residential rooftop solar PV, respectively.

Economic factors thus appear to be the primary driver of household decisions whether or not to adopt solar systems, as suggested by the results with and without the ASC. When we exclude the ASC from the model, all the weight of the choice goes onto the economic variables and vice versa. This indicates that in the stated preference environment, preferences for solar systems are highly driven by economic factors. As we move forward and interact ASC with demographic factors, we look for heterogeneity across different demographic groups. We are not just looking at how preferences for solar systems vary across groups, but also at how the economic drivers of solar system adoption play differently across different demographics.

4.2. Estimation results with interaction terms: Analysis and discussion

As shown previously in Table 6, our standard deviation results in columns 2 and 4 indicate that the estimate coefficients vary significantly across respondents; they are all strongly statistically significantly different from zero. With this in mind, our next analysis seeks to explore the nature of this heterogeneity across observable respondent characteristics (e.g. ideology, party identification, environmental motivation, and socio-demographics). A common approach to investigating this question is to look at the interaction of the ASC term with respondent-specific characteristics. All the interaction terms were specified as nonrandom variables with normal distributions. The estimation results for the model with interaction terms are presented in Table 8. We include various interaction terms of the ASC with demographic variables in the base model.[3]

In this model, all interaction terms (expressed as "ASC*Age") were statistically significant except gender and race. The negative coefficient for age explains that older respondents are less likely to choose the solar system options than young. Education, income, and children all have positive significant coefficients, indicating that more educated households, those with higher income, and those with children present are all more likely to choose solar systems than others.

Older people are less likely to adopt the solar system than young people, perhaps because the economics of these systems are less likely to work out for them. Many older people are retired and don't have disposable income to invest in solar systems. In addition, the systems take some time to pay off and older people may be less interested in those long-term payoffs. In addition, we see that income and number of children are both positively correlated with adoption, and we know that older generations, beyond a certain point, are likely to be lower income and have fewer children in the household.

In Table 9 below, we add our party identification variables using both full party identification (which uses only respondents that clearly identify as Republican, Democrat, or Independent) and "party lean" identification, a question that asks respondents which party they "lean"

Table 8
Mixed logit estimation results with interaction terms.

Variables	Mean	Standard Deviation (SD)
	(1)	(2)
Upfront Installation Cost	−0.000490***	
	(2.11e-05)	
ASC*Male	0.265	2.300***
	(0.435)	(0.845)
ASC*Age	−0.487***	0.915***
	(0.148)	(0.108)
ASC*Education	0.529***	−0.199**
	(0.122)	(0.0854)
ASC*Income	0.235*	−0.0975
	(0.127)	(0.226)
ASC*Children	1.194***	−1.532**
	(0.414)	(0.666)
ASC*White	0.312	0.594
	(0.402)	(0.590)
Average monthly savings	0.00694***	0.0220***
	(0.00202)	(0.00284)
Range monthly savings	0.000871	0.00820***
	(0.000841)	(0.00149)
AIC	5372.911	
BIC	5495.973	
Observations	10,290	10,290
Log-likelihood	−2669.4554	
LR Chi^2	1532.45	

*** Significant at 1% level
** Significant at 5% level;
* Significant at 10% level; standard errors in parentheses.

Table 9
Mixed logit estimation results with interaction terms for political variables.

Variables	Model 1		Model 2	
	(1)	(2)	(3)	(4)
	Mean	SD	Mean	SD
Upfront Installation cost	−0.000490***		−0.000488***	
	(2.13e-05)		(2.12e-05)	
ASC* Male	0.462	2.505*	0.388	2.306**
	(0.495)	(1.305)	(0.451)	(0.917)
ASC*Age	−0.610***	0.800***	−0.584***	0.812***
	(0.149)	(0.102)	(0.160)	(0.0995)
ASC*Education	0.500***	0.233**	0.424***	0.179
	(0.126)	(0.111)	(0.122)	(0.137)
ASC*Income	0.228**	0.0599	0.273**	0.201
	(0.0953)	(0.132)	(0.126)	(0.174)
ASC*Children	1.241***	1.682*	0.996**	1.623*
	(0.431)	(0.972)	(0.429)	(0.859)
ASC*White	0.435	0.729	0.424	0.674
	(0.415)	(0.548)	(0.409)	(0.726)
ASC*Democrat	**0.987****	**1.028**		
	(0.413)	**(1.033)**		
ASC* Lean Democrat			**1.164*****	**1.371***
			(0.406)	**(0.710)**
Average Monthly Savings	0.00667***	0.0222***	0.00678***	0.0208***
	(0.00201)	(0.00284)	(0.00202)	(0.00356)
Range Monthly Savings	0.000837	0.00809***	0.000776	0.00795***
	(0.000838)	(0.00154)	(0.000835)	(0.00152)
AIC	5372.656	10,290	5364.278	10,272
BIC	5510.195		5501.784	
Observations	10,290		10,272	
Log likelihood	−2667.3278		−2663.1389	
LR Chi^2	1521.13		1507.82	

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level; standard errors in parentheses.

[3] We also estimate a model that included the ASC itself in addition to interaction terms, and in that model all the results are qualitatively similar. It is not clear looking at any specification test that one model is preferred to the other. In both models the LR Chi2, log-likelihood, AIC and BIC are very close, suggesting that neither model is preferred to the other. Relative to the model presented here, the results from the model that includes the ASC only differs in that the coefficients on interaction terms for education and children in the household are not statistically significant.

Table 10
Mixed logit estimation results with interaction terms for Ideological variables.

Variables	Model 1		Model 2		Model 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	SD	Mean	SD	Mean	SD
Upfront Installation cost	−0.000489***		−0.000488***		−0.00048***	
	(2.12e-05)		(2.13e-05)		(2.11e-05)	
ASC*Male	0.534	2.395***	0.457	2.522***	0.517	2.585***
	(0.468)	(0.724)	(0.440)	(0.719)	(0.433)	(0.635)
ASC*Age	−0.372**	0.695***	−0.415***	0.701***	−0.411***	0.649***
	(0.156)	(0.143)	(0.154)	(0.169)	(0.148)	(0.136)
ASC*Education	0.588***	0.0395	0.599***	0.112	0.586***	0.152**
	(0.120)	(0.106)	(0.121)	(0.0881)	(0.119)	(0.0753)
ASC*Income	0.321***	0.0353	0.281***	0.0258	0.305***	0.000118
	(0.0988)	(0.0911)	(0.0977)	(0.0840)	(0.109)	(0.0785)
ASC*Children	0.765*	1.649*	0.754*	1.525***	0.916**	1.806***
	(0.445)	(0.872)	(0.431)	(0.536)	(0.454)	(0.559)
ASC*White	0.352	0.0751	0.492	0.150	0.362	0.0384
	(0.420)	(0.666)	(0.412)	(0.734)	(0.421)	(0.525)
ASC*Conservative	**−0.388*****	**0.638*****				
	(0.120)	**(0.134)**				
ASC*Social Conservative			**−0.324*****	**0.662*****		
			(0.123)	**(0.148)**		
ASC*Economical Conservative					**−0.283****	**0.579*****
					(0.117)	**(0.109)**
Average Monthly Savings	0.00734***	0.0217***	0.00768***	0.0212***	0.00740***	0.0210***
	(0.00200)	(0.00297)	(0.00204)	(0.00331)	(0.00196)	(0.00286)
Range Monthly Savings	0.000948	0.00783***	0.000801	0.00782***	0.000909	0.00789***
	(0.000831)	(0.00154)	(0.000835)	(0.00153)	(0.000833)	(0.00153)
AIC	5363.36		5334.194		5364.036	
BIC	5500.9		5471.633		5501.576	
Observations	10,290	10,290	10,236	10,236	10,290	10,290
Log likelihood	−2662.6801		−2648.096		−2663.0181	
LR Chi^2	1514.41		1509.27		1517.98	

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level; standard errors in parentheses.

to even if they are independent or affiliated with a smaller third party.[4] Party identification emerges as a clear indicator of motivation to adopt solar. Importantly, Mildenberger et al. have shown that while partisan affiliation is a factor in actual solar adoption, it is not a significantly large factor (Mildenberger et al., 2019). As a result, while Democrats may indicate they are willing to pay more, solar installations occur proportionately across the political spectrum.

Similarly, Table 10 shows interaction terms that include the Pew political ideology index scores ("social," "economic," and combined scores). And again, all three are robust indicators of willingness to pay. One interesting outcome is that socially conservative respondents are slightly less willing to pay than economically conservative respondents, indicating that attitudes towards solar are more about identity and values rather than the economic risk or reward.

The earlier models show heterogeneity in willingness-to-pay for rooftop solar systems. Interpretation of these interaction coefficients in terms of WTP in dollar terms is complicated, however, and it is even harder to use interaction terms to understand how demographic factors interact with other attribute variables besides the ASC. Therefore, we explore these differences further by splitting the sample into several categories and calculating the WTP using our basic mixed logit model 1.

Fig. 2 above shows calculations of WTP for split samples of the same variables included as interaction terms in Table 8 above. These reveal some extensive differences. In particular age, household children, and education emerge as variables that significantly affect willingness to pay. Gender and race differences are not as powerful in terms of WTP, but both non-white and male respondents want higher monthly savings if they are going to adopt solar. One of the most interesting results is in income, which emerges as a non-linear function. Unsurprisingly, low-income households are willing to pay less for solar. But the highest income households have less WTP than mid-income households. Affluent households show a clear affinity for the economic benefits that solar adoption may provide.

Younger householders, those under 35, have the highest estimated WTP for rooftop solar systems at more than $10,000. This is significantly higher than both of the other age groups. Further, the younger group has the lowest WTP for an additional dollar of monthly savings compared to other age groups, although this difference does not appear to be statistically significant. Younger residents appear more likely to embrace solar for non-economic reasons.

Education is also positively linked to willingness to pay. College educated respondents are willing to pay almost $2000 more than others. There is, however, substantial overlap in the range of the estimates for these two groups, suggesting that this difference may not be as significant as with age. There is little difference between these two groups in their WTP for monthly savings.

The results regarding income are less clear, with a middle-income group seeming to have the highest WTP, but with the highest income group having the greatest preference for monthly savings. It is also true that the income interaction term is only marginally significant in Table 8.

The single biggest driver of differences in WTP for residential solar systems seems to be the presence of children (under the age of 18) in the household. The presence of children drives an increase in WTP by a factor of almost 3. But, economic factors do not drive this WTP at all, with households with children demonstrating a much smaller or even negative WTP for monthly savings. Overall, these differences could be driven by many different factors which are worth exploring in future work.

Finally, even though gender and race do not show as significant in the analysis of Table 8, we do find some differences in the split sample analysis. For gender, there is basically no difference in the general WTP,

[4] Political scientists have long used "lean" party identification as a way to identify likely patterns of voting in a 2-party majoritarian system.

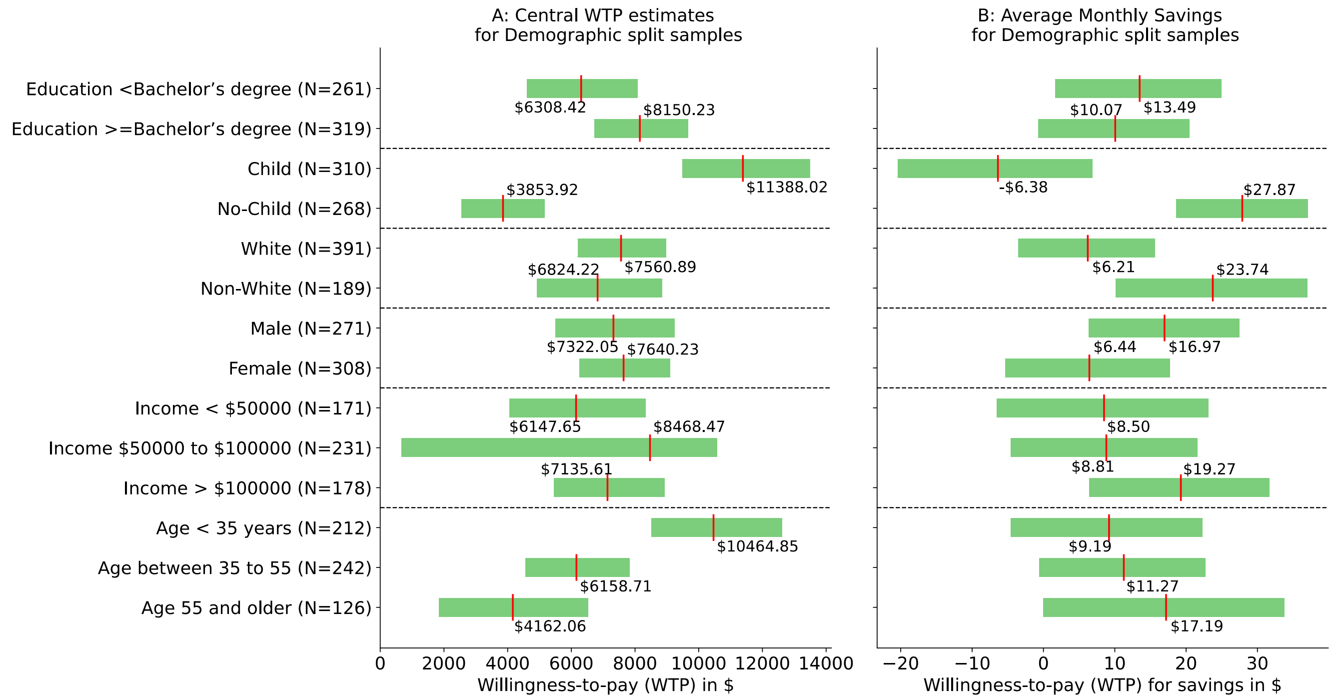

Fig. 2. Willingness to pay results with confidence intervals for Demographic Split Samples.

but males demonstrate a much higher concern for monthly savings, willing to pay almost $10 more per dollar saved each month. Similarly, there is very little difference in expressed preference for rooftop solar across white and non-white respondents, but non-whites express a much higher willingness-to-pay for monthly savings.

Importantly, these split samples are subject to omitted variables problems if different categories are correlated (age and income, for instance). As a result, the results should be interpreted with some caution. In Fig. 3 we explore this by examining combined categories across age + education, and age + income.

In general, what comes across is the importance of age as a driving factor in overall WTP. Consistently, younger groups are willing to pay more than older groups, across income and education levels. When we look at preferences towards monthly savings, however, we do find more differences with those in the "Old & High Income" category expressing the strongest preference for savings, especially compared to those in the "Old & Low Income" category, but much larger than almost any other category; the only other group that is close is the "Old & Bachelor's Degree" category which likely has a lot of overlap.

In Fig. 4 below, we present the estimated WTP results for a solar

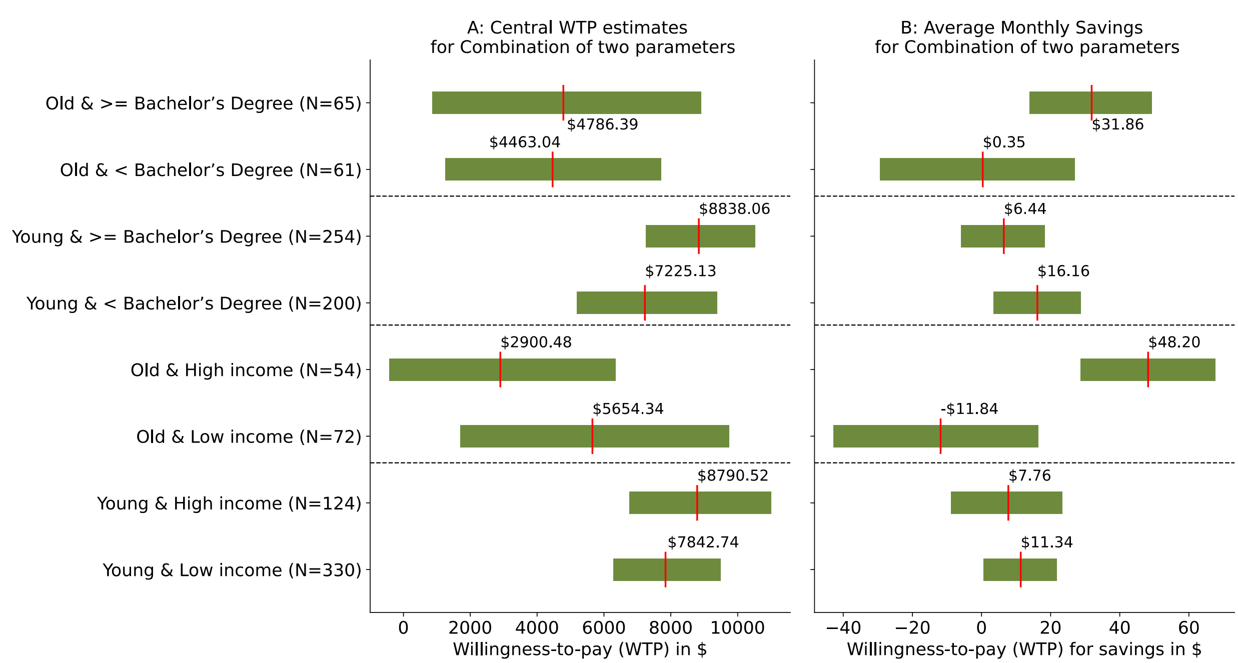

Fig. 3. Willingness to Pay Results with Confidence Intervals For Age-Income and Age-Education Split Samples.
We split the age and income sample as follows, for young and old, it is age ≤54 and age ≥55, respectively. Similarly, Low and High income is income≤ − $99,999 and income≥ $100,000, respectively.

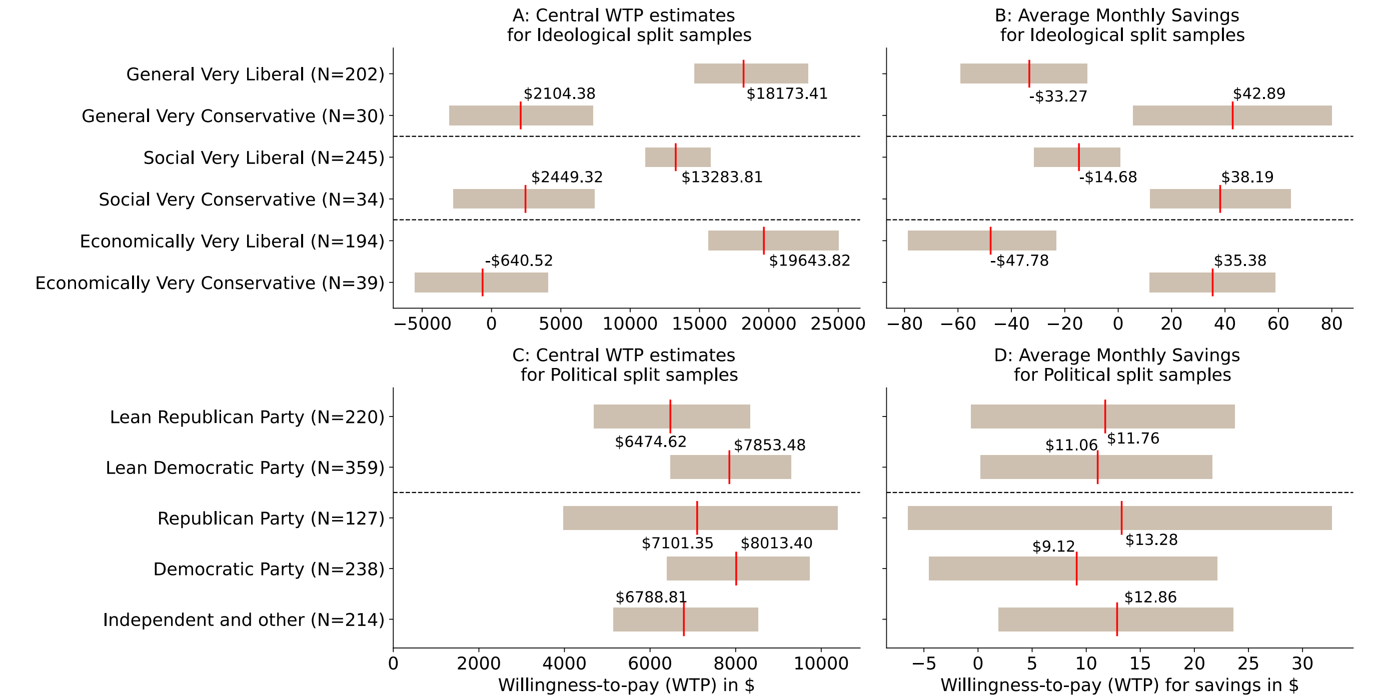

Fig. 4. Willingness to Pay Results with Confidence Intervals For Ideology and Party Identification - Split Samples.

system based on ideological and party identification split samples. Party affiliation variables are not as powerful a predictor of differences in WTP as ideology scores. While democrats and those that lean that way express a somewhat higher WTP, it is not significantly different. There is no significant difference in the estimates of WTP for monthly savings.

However, if we look at those who measure as very liberal or very conservative in general, on social issues, or on economic issues, we see consistently that the very liberal respondents are WTP much more for rooftop solar systems and care less about the economic savings associated with the systems. By contrast, conservative respondents had a low WTP for systems generally, and a high WTP for monthly savings, suggesting that preferences for solar amongst conservatives are driven by personal economic factors. The sample size for "very conservative" respondents ($N = 30$) is quite small, and caution should be used in interpreting our results for ideology because of this.

In Fig. 5, we present estimated WTP results for analyses where we split our sample of respondents according to psychological factors based on environmental motivation. Those with higher levels of integrated, intrinsic, and external motivation towards the environment all have higher WTP for residential solar systems – with large effects for intrinsic

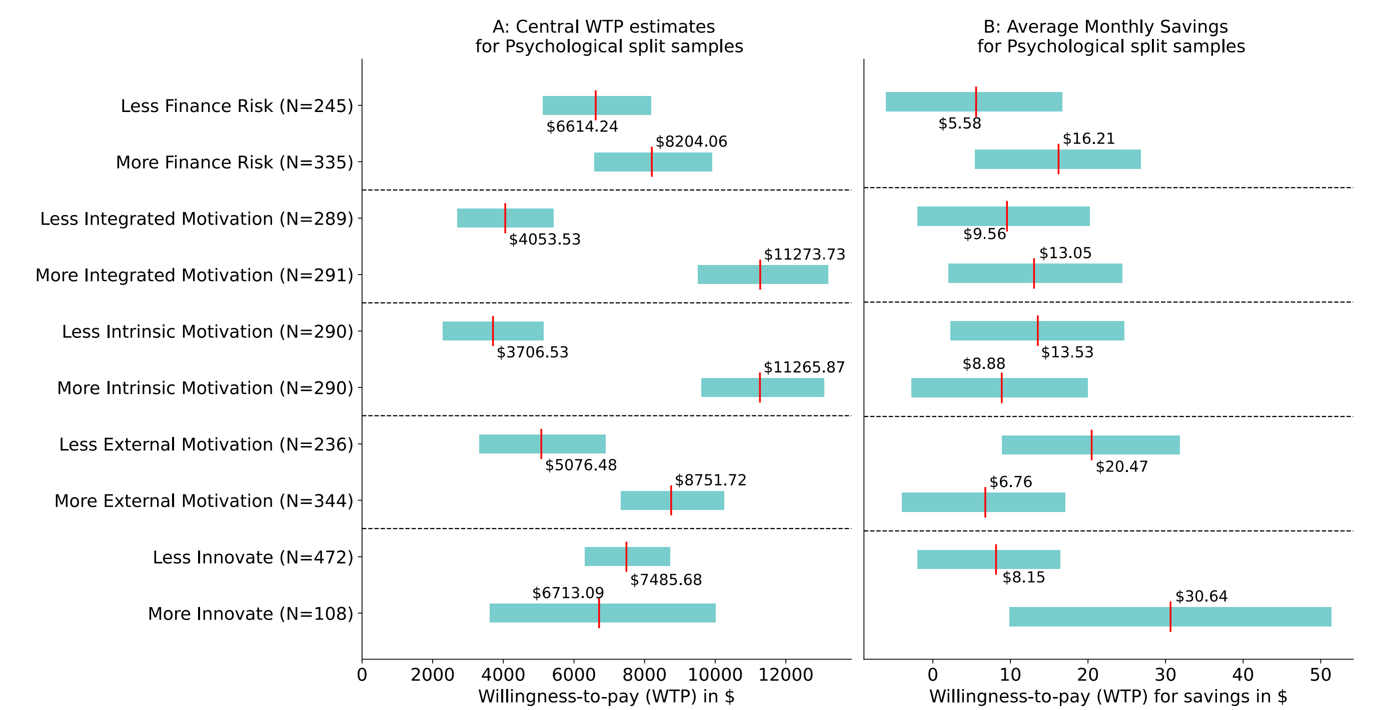

Fig. 5. Willingness to Pay Results with Confidence Intervals For Psychological Split Samples.

Table 11
Categorization of open-ended responses from adopters and non-adopters.

Adopter ($N = 88$)		Non-Adopter ($N = 577$)	
Adoption Reasons		Not interested in solar adoption (Reasons)	
Categories/Code	Description	Categories/Code	Description
Environmentally Friendly	Saving or protecting the environment, or progressive env. values	**Cost Oriented**	Costs, financing, investment payback, or savings concerns
Morally Conscious	Moral obligation, values broadly aligned with solar adoption	**Logistical Constraint**	Trees, house, neighborhood, area, the roof, lack of sunlight, not enough time
Cost Oriented	Good investment, savings, investment payback	**Unattractive / Uninterested**	Concern for aesthetics or just a lack of interest
Peer Effect	Influenced by neighborhood, friends, or someone who has installed	**Still Searching**	Lack of information or have not thought about it
Other	Undefined	**Moving**	For people who are moving or thinking about moving
		Other	Undefined

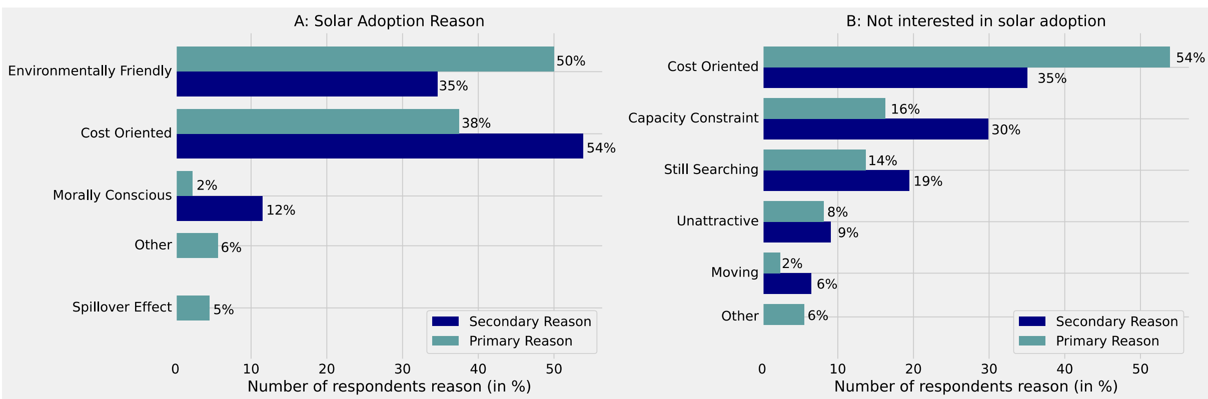

Fig. 6. Qualitative Analysis for solar adopters and non-adopters.

and integrated motivation (i.e., those with more autonomous motivation were willing to pay 2.5 to 3 times more than those with less autonomous motivation). The differences are less stark along the dimension of external motivation than the other forms, suggesting those who are motivated towards the environment out of concern about others' expectations and evaluations are willing to pay less than those who are motivated out of personal care and concern for the environment. This aligns with general findings in the environmental motivation literature suggesting that autonomous motivation is particularly important when proenvironmental decisions are costly and effortful (Green-Demers et al., 1997; Legault, 2023). There is not much difference in preferences for monthly savings, with the possible exception of external motivation where, interestingly, those with less external motivation have a higher WTP for monthly savings. This might suggest that although those who are unconcerned about others' approval are less willing to pay overall, they are more willing to pay for greater monthly return.

We also examine measures of financial risk-taking and attitudes towards innovation. We find only small differences in general WTP for systems across these dimensions. However, those willing to take more financial risk and those with higher scores for innovation are more concerned about the economic aspects of solar systems and willing to pay somewhat more for an additional dollar of monthly savings.

4.3. Qualitative analysis for solar adopters and non-adopter

In addition to our primary results, we also conduct a separate qualitative exploratory analysis of the responses to an open-ended question: "please explain why you currently choose not to install solar panels on your home." For this part of our research design, we also include results from a similar but separate survey of solar adopters to derive comparative results.

We then analyze the results to create themes amongst the responses, and test our coding using inter-rater reliability.[5] We use inductive coding to develop our thematic response categories, an appropriate method for exploratory studies (Jansen, 2020; Skjott Linneberg and Korsgaard, 2019). The respondents provided one or more reasons why they would like to adopt a solar system (using a larger set of adopter respondents) or were not interested in solar adoption. We divide codes into primary and secondary reasons and finally analyze them accordingly in the results section. The initial coding categories are shown below in Table 11.

In the left column of Fig. 6 below (part A), our data shows that people would like to adopt a solar system for two main reasons. "Environmentally Friendly" respondents care about saving the environment or protecting it. 50% and 35% of respondents say that environment is the primary and secondary reason for solar adoption, respectively. Second, cost savings are a critical reason for respondents as well including considerations for upfront installation cost, finances, investment quality, payback, or anything on savings. 38% of respondents say saving/payback is the primary reason, and 54% says that secondary reason. Almost 5% of respondents noted they would like to adopt solar because their neighbor has a solar system, or friends suggested adopting solar.

In part B, we present the respondents' primary and secondary reasons for those who are not interested in solar adoption. Upfront installation cost is the most significant barrier not to adopt a solar system. 54% of respondents say that cost is the primary reason; 35% of respondents indicate cost is a secondary reason for a solar non-adoption. We see some responses worried about the roof damage after the solar

[5] Inter-rater reliability is often discussed in a situation where two or more individuals (or raters, examiner) agree on subjective judgment on the same targets. Most studies use two raters to assess all targets in the Inter-rater reliability technique (Perry and Henry, 2004).

installation or general concerns for tree cover, lack of sunlight. Some respondents are still looking for a better deal or learning about solar systems.

5. Conclusion and policy implications

The current study provides concrete information about American consumers' willingness to pay for solar panels, and also offers a detailed assessment of the many social, demographic, ideological, and motivational factors that affect this willingness to pay. It also provides some of the first analysis that helps us understand tradeoffs between upfront payments versus monthly savings, and tolerance of risk in payment variation. This analysis has a variety of implications for increasing the adoption of solar, and for policymakers and other key stakeholders to consider in policy design, outreach to homeowners, and consideration for financial incentives.

Our analysis is highly suggestive that the economics of solar systems are a key, if not the key, driver of adoption decisions. This means that policy making that is clearer about expected costs, expected savings, and that addresses the initial investment could have a significant impact on potential solar adoption. More specific information about actual willingness to pay should help policymakers adjust the appropriate amount of financial incentives for solar. If incentives are too small, governments will find that solar adoption will not proceed as quickly as is necessary. Alternately, if subsidies are too high to motivate adoption, then we will see inefficient spending. It is critically important to get the economic incentives right in encouraging household adoption of solar systems.

We also see significant differences in willingness to pay along a variety of demographic lines. Policymakers and solar program decision makers could focus outreach efforts on specific demographic "types." For instance, one could imagine a "Look who's going solar" campaign that highlighted solar adoption amongst older homeowners, or which emphasized near-term benefits to that part of the population. A similar approach could be used along ideological or party identification lines, using targeted messaging that was designed to break across the stereotypical ideological ideas of the typical Republican or Democratic homeowner. For instance, one could imagine campaigns that emphasized the value and usefulness of solar adoption to "working class" ideals, or to emphasize solar as a way to achieve energy independence or other affiliated self-reliance concepts for conservatives.

Our results underscore that autonomous proenvironmental motivation plays an important role in willingness to pay for solar. When it comes to policy, legislation, messaging, and education, it is likely that the continued encouragement and support of individuals' concern for environmental preservation and sustainability may remain one of the best ways to promote high cost adoptions like solar PVs. Research in environmental motivation has also shown that messaging which "activates" or targets underlying potential for autonomous motivation and action has been effective when it provides meaningful rationale for engagement or when it is linked with other values that respondents favor (see Legault, 2023 and Pelletier and Sharp, 2008 for reviews). Messaging that emphasizes solar as a way to improve health by reducing air pollution, or increases one's ability to be resilient to large storms could be effective in helping to develop and/or increase motivation for solar adoption.

Our qualitative analysis demonstrates that a significant proportion of both adopters and non-adopters are choosing solar for financial reasons, and that those with less willingness to pay are worried about cost. Encouragingly, overall willingness to pay is relatively high compared to the average cost of a rooftop solar system (in 2021 average U.S. cost was \$3000 per kw on an average installation of 6 kw). Typical payback times in the U.S. range from 8 to 11 years.

Future work can address the question of ideology to a greater degree than shown here by obtaining larger sample sizes across the ideological spectrum, allowing for better interpretation. Further, additional research is needed to examine interaction effects between motivational reasoning and ideology in the context of energy transition technologies. Finally, we hope to address further questions concerning homeowner interest in other market models for adopting solar such as co-ops and community solar models, and well as additional infrastructure and contextual factors.

Addressing climate change and the variety of other problems associated with fossil-fuel generation of electricity is going to require success across a wide range of policy mechanisms. Residential solar adoption will be a critical part of that effort. Improving our understanding of the factors that drive adoption is an important part of this endeavor. By evaluating a wide range of demographic, personal, political, and motivational predictors, this analysis offers a uniquely comprehensive account of the way different types of homeowners think about the solar adoption marketplace.

CRediT authorship contribution statement

Sachin B. Badole: Conceptualization, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing - original draft, primary, Writing - review & editing. **Stephen Bird:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Martin D. Heintzelman:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Lisa Legault:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

None.

Appendix 1. Data quality protocol

While conducting the qualitative analysis, we found that some respondents provided similar line answers.[6] In Table I-1, we omitted 156 answers due to "straight-lining" and other clear data quality concerns.

Again, we have checked each respondent's other open-ended question responses, zip code, and Internet Protocol address (IP address) for further robustness. First, we found that some respondents were from out of New York State, which violates one of our constraints. Therefore, we omitted a total of 179 non-New York observations. Second, according to a similar IP address, we observed that 18 respondents did the survey twice. In previous research (Bowen et al., 2008), IP address was used to identify repeat responders. Also, SurveyMonkey tracks the IP address of individual respondents to avoid multiple or duplicate submissions (Wilson, 2021). We found that 18 respondents provided multiple submissions. Therefore, we decided to

[6] In our survey, we asked one question regarding solar installation reasons to those households that had already adopted solar. For instance, this question, "Why did you choose to have them (solar panel) installed?". We found that many respondents provided identical word for word answers for this question. For example, the "Save Thousands of Dollars" appeared 32 times, the "Start Saving from Day 1" appeared 12 times, and many more. Therefore, we omitted these respondents from our final data.

omit one of the responses from each of these 18 respondents. Finally, we have 88 solar adopters and 580 solar non-adopters. Our choice experiment was only conducted on the 580 non-adopters.

Table I-1
Data Integrity Results.

	Survey Type			
	Solar Adopter	Solar Non-Adopter		
Data type and reason for omitted data	Solar Adopter (Survey Monkey)	Solar Non-Adopter (Qualtrics)	Solar Non-Adopter (Survey Monkey)	Total Observations
Raw Data	408	421	192	1021
Omitted False (Similar Response)	154	0	2	156
Omitted Non-New York Response	165	7	7	179
Omitted One of IP Address response from duplicate IP Address	1	2	15	18
Clean New York Data	88	412	168	668
Total Clean	88	580		

Table I-2
Descriptive Statistics.

Variable		**Adopters**			**Non-Adopters**			**All**		**New York Census**[a]
Categories	Count	Percent	Obs.	Count	Percent	Obs.	Count	Percent	Obs.	Percent
Gender										
Male	37	42%	88	271	47%	580	308	46%	668	48.9%
Female	50	57%		308	53%		358	54%		51.1%
Other	1	1%		1	0.2%		2	0.30%		–
Income										
$0–9999	1	1%	86	10	2%	575	11	2%	661	6.8%
$10,000–24,999	0	0%		43	7%		43	7%		10.8%
$25,000-49,999	2	2%		118	21%		120	18%		15.8%
$50,000-74,999	13	15%		122	21%		135	20%		14.3%
$75,000-99,999	15	17%		109	19%		124	19%		11.6%
$100,000-124,999	14	16%		55	10%		69	10%		16.4%
$125,000-149,999	4	5%		42	7%		46	7%		
$150,000-174,999	16	19%		20	3%		36	5%		9.4%
$175,000-199,999	10	12%		18	3%		28	4%		
$200,000 and up	8	9%		29	5%		37	6%		15.0%
Prefer not to answer	3	3%		9	2%		12	2%		–
Education										
No High School	0	0%		1	0.2%		1	0.2%		12.10%
Some High School	0	0%		4	0.7%		4	0.6%		
High School Degree	1	1%		72	12%		73	11%		24.57%
Some College Degree	4	5%	88	105	18%	578	109	16%	666	23.32%
Associate Degree	6	7%		79	14%		85	13%		–
Bachelor's Degree	42	48%		181	31%		223	33%		22.29%
Master's Degree (Professional)	28	32%		112	19%		140	21%		17.70%
Doctorate Degree	7	8%		24	4%		31	5%		–
Ethnicity										
White	71	81%		391	67%		462	69%		52.9%
Black	2	2%		62	11%		64	10%		13.4%
Hispanic or Latino	14	16%		78	13%		92	14%		19.7%
Mid-Eastern	0	0%		0	0%		0	0%		–
East Asian	0	0%	88	28	5%	580	28	4%	668	9.0%
South Asian	0	0%		6	1%		6	1%		
Native American	0	0%		3	0.5%		3	0.5%		0.2%
Other (please specify)	0	0%		10	2%		11	2%		4.8%
Prefer not to answer	1	1%		2	0.3%		2	0.30%		–

Note: This table is to be continued in the below Table I-3. Rounding used in percentages.

[a] Source: U.S. Census Bureau, American Community Survey 1-Year Estimates Data Profiles, Table DP05 (2022), Table B06009 (2022), Table S1901 (2022), Table S0901 (2022); retrieved from https://data.census.gov

Table I-3
Descriptive Statistics (Continue).

Variable	Adopters			Non-Adopters			All			New York Census
Categories	Count	Percent	Obs.	Count	Percent	Obs.	Count	Percent	Obs.	Percent
Age										
18–24	4	5%	88	93	16%	579	97	15%	667	6.6%
25–34	31	35%		147	25%		178	27%		14.0%
35–44	12	14%		113	20%		125	19%		12.9%
45–54	20	23%		115	20%		135	20%		12.2%
55–64	18	20%		79	14%		97	15%		13.3%
65–74	3	3%		28	5%		31	5%		10.3%
75 or older	0	0%		4	0.7%		4	0.6%		7.7%
Children[a]										
1 Child	41	47%	88	166	29%	579	207	31%	667	26.1%
2 Children	19	22%		83	14%		102	15%		
3 Children	24	27%		43	7%		67	10%		
4 Children	3	3%		13	2%		16	2%		
5 Children	1	1%		5	0.9%		6	0.9%		
6 or more Children	0	0%		1	0.2%		1	0.15%		
No Children	0	0%		268	46%		268	40%		73.5%
Political[b]										
Republican Party	10	11%	88	127	22%	579	137	21%	667	21.92%
Democratic Party	52	59%		238	41%		290	43%		50.6%
Independent and other	26	30%		214	37%		240	36%		27.46%
Lean Republican	12	14%	86	220	38%	579	232	35%	665	28%
Lean Democrat	74	86%		359	62%		433	65%		53%
No Lean	–	–		–	–		–	–		19%

[a] Source: Statistical Atlas, https://statisticalatlas.com/place/New-York/New-York/Household-Types
[b] Source: WKBW7 News Buffalo, (Erbacher, 2020); Pew Research Center: https://www.pewresearch.org/

Table I-4
Descriptive Statistics for Ideological variables (non-Adopters).

Variable	Non-Adopters		
Categories	Count	Percent	Obs.
Ideology			
1 Very Liberal	202	35%	
2 Liberal	67	12%	
3 Moderate Liberal	45	8%	
4 Neutral	145	25%	580
5 Moderate Conservative	42	7%	
6 Conservative	49	8%	
7 Very Conservative	30	5%	
Economic Ideology			
1 Very Economically liberal	194	33%	
2 Economically Liberal	54	9%	
3 Moderate Economically Liberal	50	9%	
4 Neutral	127	22%	580
5 Moderate Economically Conservative	59	10%	
6 Economically Conservative	57	10%	
7 Very Economically Conservative	39	7%	
Social Ideology			
1 Very Socially Liberal	245	42%	
2 Socially Liberal	55	10%	
3 Moderate Socially Liberal	35	6%	
4 Neutral	121	21%	577
5 Moderate Socially Conservative	49	8%	
6 Socially Conservative	38	7%	
7 Very Socially Conservative	34	6%	

In this study, we have three primary variables of interest: "Upfront Installation Cost", "Average Monthly Savings", and "Range Monthly Savings". To sensitivity check, in Fig. F-1, we plot the estimated coefficient with a 95% confidence interval for different specification models. We found that they are consistent across all models except Table 6 Model 2 when we exclude the ASC magnitude of the estimated coefficient increase. We also provide similar coefficient plots for demographic, political, and ideological variables in Figs. F-2 and F-3.

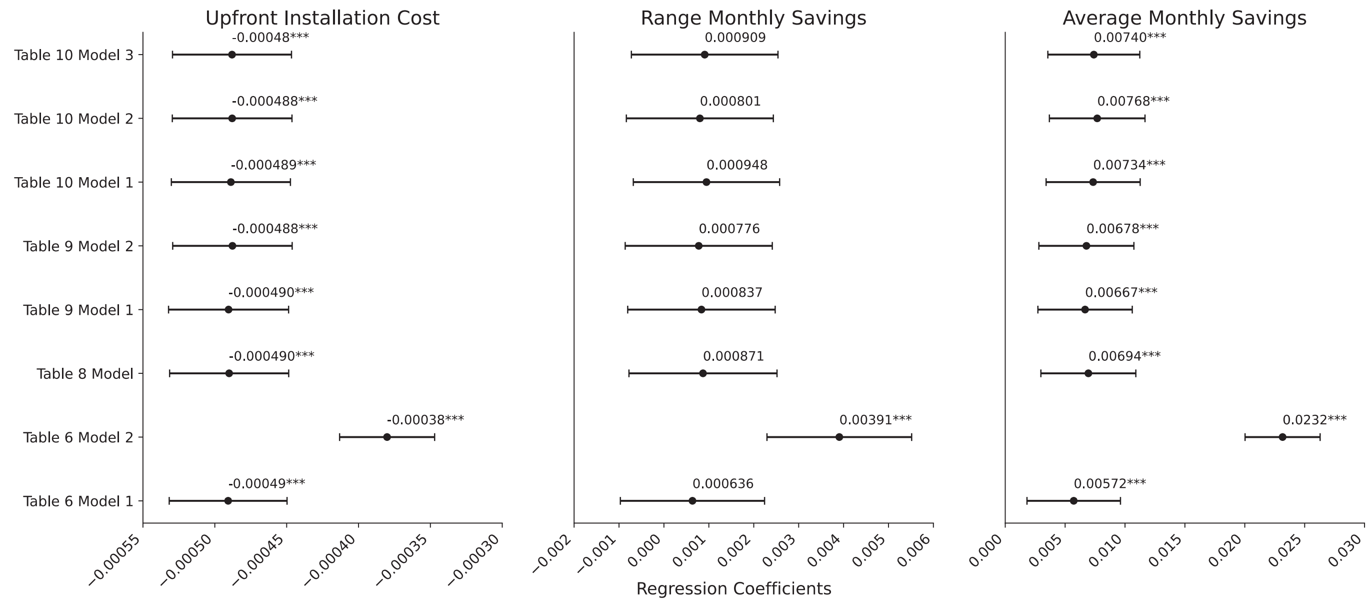

Fig. F-1. Estimated results with confidence intervals for main variable of interest.

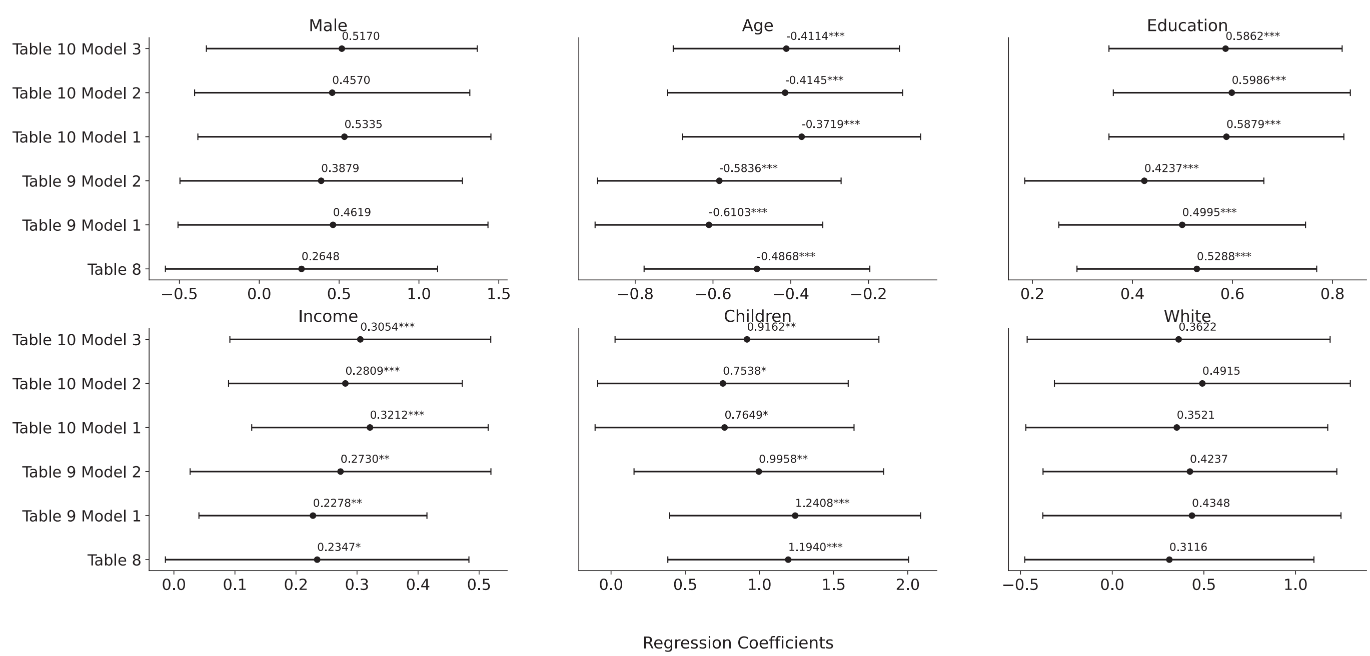

Fig. F-2. Estimated results with confidence intervals for demographic variables.

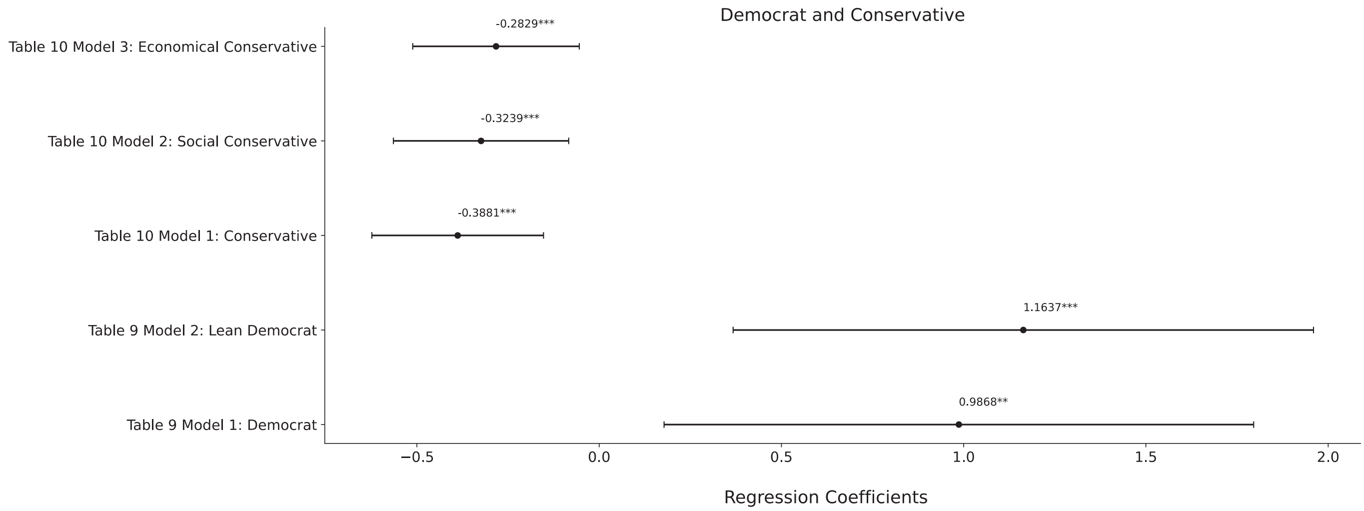

Fig. F-3. Estimated results with confidence intervals for Democrat and Conservative variables.

Table I-5
Various studies on WTP for renewable energy adoption.

Author	Research Objective	Data	Country	Survey	Methodology	Findings
(Mozumder et al., 2011)	Estimate households' WTP for renewable energy allocation of 10% and 20% of renewable energy supply.	367 Survey responses	Southwestern State, New Mexico, USA	A web-based survey from New Mexico residents	CV method, Tobit model, Heckman selection model	WTP was positively related to environmental concerns, altruism related to environmental causes, Income, and household size. WTP $5.77/month for 10% and $15.04/month for 20%, after correcting hypothetical bias.
(Yoo and Kwak, 2009)	The main goal of this research is to measure the economic benefits of increasing the consumption of green electricity by households.	800 Survey responses from the metropolitan area	Incheon, Gyeonggi, and Seoul, Korea	Face-to-face interviews	CV method, Conventional model, Spike model	After introducing the policy that increases consumption of green electricity from 0.2% to 7% by 2021 by households. Mean WTP from parametric method $1.8/month. Mean WTP from non-parametric method $2.2/month.
(Zhang and Yang, 2012)	This study focuses on recognizing market segments and finding the WTP for green electricity	1139 valid responses	Jiangsu, China	e-mail & mail survey in an urban area.	CV method, multinomial logit (Mlogit) model	Mean WTP ranges from $1.15 to $1.51 per month. Some subjects with high Income and higher education desire higher WTP to lower WTP propose that green electricity is a luxury good.
(Nomura and Makoto, 2004)	Estimate WTP for photovoltaic and wind-turbine energy.	370 consumers response	Japan	Mail survey	CV method	Median WTP for PV and wind energy is $17/month from each household.
(Borchers et al., 2007)	Evaluate consumer preferences and WTP for voluntary participation in green electricity program and compares them to solar, wind, methane, & biomass (WTP).	625 Survey responses from New Castle County, Delaware	Delaware, USA	Face-to-face Interviews at the Department of Motor Vehicle (DMV)	CE method, Nested logit (NL) model	Positive WTP for green energy electricity. Respondents prefer solar over generic green and wind. WTP ranges from $6.10 to $31.16 for a 10% solar generation program. (Voluntary program)
(Bao et al., 2020)	How do consumers prefer solar adoption and non-adoption?	1053 homeowners in California, & 720 homeowners in Massachusetts	California and Massachusetts, USA	Peanut Labs, Qualtrics, an online market research company	Discrete CE method, Hierarchical Bayes (HB) model, logit model	They found that solar owners viewed installer reliability as more important than cost.
(Mabile, 2021)	Study consumers' preferences towards solar PV or characteristics of solar PV. Explore WTP for solar PV.	697 responses from Atlanta and 602 responses from Boston	Boston and Atlanta, USA	Amazon Mechanical Turk	CE method, Conditional logit model	The upfront cost is a hurdle for consumers to adopt solar PV. Positive neighbor effect. Atlanta and Boston's consumers are WTP $4700 and $5500 for a solar PV, respectively.

(continued on next page)

Table I-5 (*continued*)

Author	Research Objective	Data	Country	Survey	Methodology	Findings
(Dong and Sigrin, 2019)	Develop a "parameterization + calibration" approach deals with the stated-intention and omitted-variable biases and explores consumers' WTP for solar PV.	10,064 PV adopters in San Diego. 400 responses from four states	USA	SurveyGizmo and Qualtrics	NREL's dSolar model	Adopters expect a payback time of 5 to 10 years, and non-adopter expect a payback time shorter than 5 years. The "Parameterization + calibration" approach improves compared to other old methods for estimating WTP.
(Goett et al., 2000)	Estimate WTP for retail energy suppliers.	1205 consumers interviewed	USA	Phone-mail-phone survey	CE method, Mixed logit model	WTP for a local presence is 1.2 cents/kWh.
(Zorić and Hrovatin, 2012)	This study explores WTP for green electricity.	450 respondents	Slovenia	Internet and field survey	The Tobit regression model, Double-hurdle model	The results confirm that age is **negatively** related to the WTP for green electricity. But Income, education, and environmental awareness **positively** affect the WTP for green electricity.
(Lin and Kaewkhunok, 2021)	Find the relation between the ethnic-case factor and the adoption of solar power technology.	6000 household responses from urban and rural areas.	Nepal.	A cross-sectional survey	Propensity score matching	The results show that compared to high caste households, Dalit and Madhesi households, which are the lowest caste and most marginalized ethnic group in Nepalese society, were about 36.3% and 79.8% less likely to adopt solar power technology.
(Roe et al., 2001)	Find WTP for environmental attributes.	1001 adults from shopping malls in 8 different cities.	USA	Conjoint survey	Simple hedonic regression (OLS)	Across all demographic groups, people are willing to pay a median of \$0.38 to \$5.66 annually for a 1 % decrease in air emissions.

Note: PV- Photovoltaics, CE- Choice Experiment, CV- Contingent Valuation, and WTP- Willing to Pay, NREL- National Renewable Energy Laboratory, Four States- (California, Arizona, New Jersey, New York), OLS- linear ordinary least squares.

Appendix 2. The discrete choice/random utility framework

This study uses a discrete choice experiment (DCE) method and mixed logit model to estimate the household WTP for a residential rooftop solar system. Discrete Choice is based on the random utility theory developed by McFadden in the 1970s (Domencich and McFadden, 1975; McFadden, 1996, 1974) which predict choices amongst discrete sets of alternatives and where respondents choose the alternative with the most significant utility. As stated by the Random Utility Theory, consumers make the decision of their choice by considering the attributes of the goods and the related prices to maximize their utility (Lancaster, 1966; Sammer and Wüstenhagen, 2006). Since respondents are also presumed to have incomplete information, the utility considers random variable to consider this uncertainty.

Train derived the mixed logit identification in the context of repeated choices by respondents with continuous taste distributions, the so-called panel mixed logit (K. E. Train, 2009). Let n denote that individual respondents were asked to respond to a discrete choice question. In standard stated choice analysis, the respondent is presented with J hypothetical alternatives, $j = 1, \dots, J$ and is asked to select one of them. In the choice set, respondents n have observed personal attributes and stated alternative characteristics. In this study, the alternatives may differ in terms of the upfront installation cost, saving on the electricity bill, and payback period. The utility that the respondent n associates with the alternative j, in every single decision is given as:

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \tag{1}$$

Where, j is one of three choice alternatives in our choice questions (i.e., Install A, Install B, Don't Install), U_{nj} represents the utility for respondent n obtains from the alternative j, x_{nj} represents the observed variables that include demographics, political affiliation, ideological, and psychological variables for respondent n in data. β_n is a vector of coefficients of the observed variables for respondents n. ε_{nj} is the error term, and is considered to be independent & identically distributed (IID) as a Type I Extreme value. Luce's Axiom of Choice states that the probability that a respondent chooses choice A over B will not change if another third alternative is added to the choice question (Luce, 1959). This is also known as the independence of irrelevant alternative (IIA) assumption. Another assumption is that the error terms for respondents are IID under the conditional logit model, which considers that all respondents would like the same preferences.

In the following eq. (2), the respondents choose the alternative i with the highest utility, maximizing respondents' utility while deciding on a discrete choice setting.

$$U_{ni} > U_{nj} \forall j \neq i \tag{2}$$

The conditional on β_n, the logit probability that respondents n sequence of choices the alternative i is the product of standard logit formulas:

$$L_{ni}(\beta_n) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{nj}}} \tag{3}$$

The unconditional choice probability becomes the integral of the logit probability of $L(y_n|\beta_n)$ overall values of β_n weighted by its density:

$$P_{ni} = \int \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} f(\beta)\, d\beta \tag{4}$$

Where $f(\beta)$ is the density of β_n which depends on parameters to be estimated. This unconditional probability is called the mixed logit choice probability since it is a product of logits mixed over a density of random factors reflecting tastes. We used the simulation approach as proposed by Brownstone and Train (1998), in which they discussed that the integral does not have a closed-form solution; hence the integral is approximated through simulation over repeated draws. The mixed logit model gave better results than the multinomial or conditional logit model. Because in our discrete choice setting, we asked several choice questions (i.e., 18 choice sets) per respondent, that repeated choice set to relax the assumption that all respondents have the same preferences.

Based on the linear utility functions assumption, we estimate the WTP in eq. 5, where β_k indicates the coefficient for the service attribute k and β_{price} is the price coefficient. According to Holmes et al. the price coefficient is uniform across respondents (Holmes et al., 2017). Considering this assumption, respondents are indifferent between that price change and a unit change in the attribute while the change in the price of attribute k and it represents as:

$$WTP_k = -\frac{\beta_k}{\beta_{price}} \tag{5}$$

Train and Weeks, 2005 illustrate two methods to estimate the WTP for given goods (Train and Weeks, 2005). First, as defined in eq. (5), estimate a discrete choice model in the "preference space" where parameters have units of utility and then compute the WTP by dividing the parameters by the price parameter. Second, estimate a discrete choice model in the "WTP space" where parameters have units of WTP. In this paper, we estimate respondents' marginal willingness to pay in the "preference space" for different attributes of the solar system. The two procedures generally produce the same estimates of WTP for homogenous models. We also run the base model in "WTP space" and find similar results as a robustness check.

Appendix 3. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107703.

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